



Competition and transmission evolution of global food trade: A case study of wheat

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HIGHLIGHTS

- Competitive relationship of global wheat trade is considered in this study.
- A wheat-trading competition network is constructed using complex network.
- A novel indicator “competitive intensity” is introduced in this paper.
- Large wheat importers play important roles for evolution of the competition pattern and transferring wheat-trading competition.

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ABSTRACT

Food trade plays an important role in improving each country's food security, and will be even more critical under climate change. Previous literature mainly analyzed the evolution of global food trade from the view of importers with less attention to the possible competitive relationships among importers. In this paper, we explored global food trade from the perspective of competition and investigated regions and countries' adaptive behaviors to enhancing food security in relation to weather patterns, which is relevant to climate change. We collected global wheat trade data from the UN Comtrade database and constructed wheat-trading competition networks. We studied overall features, core-periphery structure (differentiating the whole network into two groups: the core and the periphery) and the evolution of the network over time. The results revealed that wheat trade had formed a global competition pattern, while the number and tightness of competitive relationships gradually decreased with time. A second finding was that core countries and periphery countries were clearly identified in the wheat competition network. Large wheat importers such as Italy, Egypt, Japan and Algeria, were the main driving force for evolution of the competition pattern and played important roles in transferring wheat-trading competition. Finally, a targeted policy framework was put forward to promote the stability and healthy wheat-trading environment.

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1. Introduction

With economic development in agricultural technology, the past half-century has seen marked growth in food production, allowing for a dramatic decrease in the proportion of the world's people that are hungry, despite a doubling of the total population [1]. However, climate change can strongly impact food production [2–4], influencing global food security [5,6]. Today 795 million people still do not have access to sufficient protein and energy from their diet, and even more suffer from some form of malnourishment [7]. Meanwhile, most food consumed worldwide is grown locally. Where there is not enough local production to meet demand, trade has been instrumental in filling the gap and further plays an important role to enhance each country's food security [8].

In recent decades, a number of researchers have examined whether food trade influence food security. Dorosh [9] analyzed how rice trade liberalization between Bangladesh and India affected national food security, with results indicating that trade liberalization offered potential benefits for food security by enabling a rapid increase of food supply. Tanaka [10] used a Computable General Equilibrium (CGE) model with a Monte Carlo simulation to quantify the impacts of rice trade on national food security and found little evidence of Japan suffering from trade shocks. Asche [11] studied the relationship between food security and the global trade of fish and seafood between developing and developed countries. The results showed that developing countries exporting high-quality seafood in exchange for lower quality seafood would not have bad effects on food security. Meanwhile, other researchers considered complex trade relationships as a whole system and applied complex network theory, which is widely applied in different fields [12–17], to analyze the global trade relationships of food and their derivatives (like “virtual water”, that is water resources used to produce food commodities) [18–23].

Owing to the different natural conditions and agricultural technology, grain production varies dramatically among countries. Take wheat as an example, a small group of countries, such as the US and Canada, contribute most of world's wheat production, which leads to several countries importing wheat from the same exporter and forces them to compete with each other. Previous researches using complex network theory mainly analyzed the evolution of food trade. In this paper, we attempt to analyze such competition from the importers' perspectives (demand side). In addition, previous literatures adopting complex network theory mainly focused on the networks' structural characteristics, while only a few works [22–25] studied trade policy of food security based on these analysis. In global food trade system, identifying dynamic competitive relationships and studying the path of its evolution are of great importance for food importers to master new rules of global food trade and develop import strategies that not only enhance competitiveness but also create healthy competition within global food trade and ensure global food security, especially under climate change.

This paper focuses on wheat, the largest trade volume of crops and an important commonly imported food [8,26]. Besides, the studies of global wheat trade and production have attracted much scholars' attention for decades [27–30]. Therefore, we constructed global competitive wheat networks and studied the overall features, core–periphery structure (differentiating the whole network into two groups: the core and the periphery) and the evolution of network over time. Meanwhile, we address the following questions: What are the main features of global competition network for wheat? Which regions play significant roles and dominate the wheat competition network? Which competitive intensities among countries are strong and which countries face severe wheat insecurity?

This study contributes to the literature in three aspects. First, we apply complex network theory to analyze the overall features and evolutionary patterns of the wheat trade network from a competition perspective, which has received little attention in the existing literature. Second, considering the difference of network links, a new indicator, i.e. competitive intensity, is introduced in the wheat-trading competition network. The competition is divided into two types: direct competition and indirect competition. Third, a targeted policy framework is proposed to promote the stability and healthy evolution of wheat-trading competition.

The rest of the paper is organized as follows. Section 2 defines the trade network and proposes the indicators for network analysis. Then, the empirical analysis and results of wheat trade network are discussed in Section 3. We conclude with some policy suggestions and future research directions in Section 4.

2. Models and methods

2.1. Competition network modeling

We take global wheat-trading competition as a network and apply the set $G = (V, E)$ to describe, where wheat importers $V = (v_1, v_2, \dots, v_n)$ are represented as competition network nodes, and competitive relationships $E = \{e_{ij}\}$ are denoted as network links, where a link represents the competitive relationship between countries. If countries v_i and v_j import wheat from the same country, $e_{ij} = 1$, otherwise, $e_{ij} = 0$. We only consider competitive relationships and construct a wheat-trading competition network based on whether wheat importers have the same exporter to study the structural evolution of the wheat-trading competition pattern. Besides, due to the differences in import sources and import volume, the levels of competitiveness may be different for different competitive relationships. Thus, we further take indicator “competitive intensity” as the links' weights (a large value of weight means high level of competitiveness) and construct a wheat-trading weighted competition network. Moreover, the evolution of the global wheat-trading competition is explored based on the weighted competition network.

2.2. Wheat-trading competition network

Based on the wheat-trading competition network, we analyze the overall characteristics of the competition network from four indicators (degree, density, clustering coefficient, and average path length).

(1) Degree

In the wheat-trading competition network, the degree of a wheat importer (k_i) is defined as the number of countries that have competitive relationships with v_i and the definition is as follows [31]:

$$k_i = \sum_{j=1}^n e_{ij}, \quad (1)$$

where n denotes the total number of countries, and e_{ij} refers to the link between countries v_i and v_j .

(2) Density

The density indicator is used to measure the overall network's competitiveness. A large density value indicates fiercely competitive relationships in the network. For wheat-trading competition network, if there are m links and n countries in the network, the density φ is defined as follows [32]:

$$\varphi = \frac{2m}{n(n-1)}, \quad (2)$$

(3) Clustering coefficient

If two countries have competitive relationships with a third country v_i , the clustering coefficient indicator can be used to evaluate the probability that these two countries also have a competitive relationship with each other. A large value of clustering coefficient (c_i) indicates that the country's (v_i) neighbors (countries that connect with country v_i) fiercely compete with one another. The indicator for a given country can be presented as [33]:

$$c_i = \frac{2a_i}{k_i(k_i-1)}, \quad (3)$$

where n denotes the number of countries, k_i refers to the degree of country v_i , and a_i indicates the number of links among the neighbors of country v_i . The average network clustering coefficient $\bar{C}$ is presented as:

$$\bar{C} = \frac{1}{n} \sum_{i=1}^n c_i, \quad (4)$$

(4) Average path length

The average path (meaning a sequence of links that connect a sequence of nodes in the network) length is the average number of links along the shortest paths for all possible pairs of competition network countries. A short average path length means strongly competitive pressure. The average path length is defined as follows [33]:

$$L = \frac{1}{n(n-1)} \sum_{i,j} d_{ij}, \quad (5)$$

where d_{ij} denotes the shortest path (minimum number of links) between country v_i and country v_j . If $v_i = v_j$ or v_i cannot reach v_j , we assume that $d_{ij} = 0$.

(5) Core-periphery model

In the network, there might be some nodes that are closely connected with each other and also connected with other nodes, and the group (or core) that consists of these nodes would play a particularly important role in the formation of the competition pattern. The core-periphery model, which has been widely employed in previous work [34–36], is applied to detect densely-connected “core” and sparsely-connected “periphery” portions of the network in this work. The main idea of detecting the core-periphery structure is to note how well the current structure approximates an ideal core-periphery structure, which can be observed through the unnormalized Pearson correlation coefficient (ρ , which can be thought of as the fitness between the real structure and an ideal core-periphery structure). If $\rho = 1$, the structure is the ideal core-periphery structure, which means there are two groups, the core in which nodes are fully connected with each other and the periphery in which nodes are not connected with each other. For example, Freeman's Star [31] is a typical ideal core-periphery structure, which nodes (from two to five) connected with node one, but they do not connect with each other. See Fig. 1.

In this paper, we apply the core-periphery detection algorithm proposed by Borgatti and Everett [37], which can improve the fitness in contrast to other algorithms of the discrete core-periphery model. The indicator (unnormalized Pearson

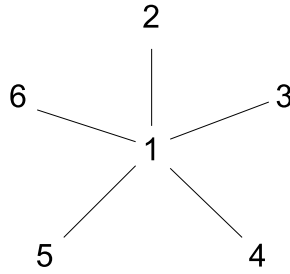


Fig. 1. Freeman's Star.

correlation coefficient) is defined as follows:

$$\rho = \sum_{i,j} e_{ij} \delta_{ij},$$

$$\delta_{ij} = \begin{cases} 1 & \text{if } g_i = \text{CORE and } g_j = \text{CORE,} \\ 0 & \text{if } g_i = \text{PERIPHERY and } g_j = \text{PERIPHERY,} \\ \bullet & \text{otherwise,} \end{cases} \quad (6)$$

where ρ represents the unnormalized Pearson correlation coefficient, e_{ij} indicates the link between v_i and v_j , g_i (g_j) refers to the group (core or periphery) that country v_i (v_j) is assigned to, δ_{ij} indicates the presence or absence of a tie in the ideal core-periphery structure and “ $\bullet$ ” stands for a missing value. ρ achieves its maximum value when and only when $\mathbf{E}$ (the matrix of e_{ij}) and Δ (the matrix of δ_{ij}) are identical, which occurs when $\mathbf{E}$ has an ideal core-periphery structure.

2.3. The wheat-trading weighted competition network

The competition network defined in previous section considers the competitive relationship among countries but does not consider the intensity level of different competitive relationships (links' weights). Thus, in this section, we differentiate these links and introduce the indicator proposed by Glick and Rose [38] to measure the competitive intensity. We adopt the competitive intensity as the weights of network links and construct a weighted network to analyze the dynamics of wheat-trading competition.

We focus on two types of competitive intensity: direct competitive intensity and indirect competitive intensity. The direct competitive intensity is given as follows:

$$S_{ij}^{\text{direct}} = \sum_k \left\{ \left(\frac{Y_{ki} + Y_{kj}}{Y_t} \right) \times \left[1 - \frac{|(Y_{ki}/Y_i) - (Y_{kj}/Y_j)|}{(Y_{ki}/Y_i) + (Y_{kj}/Y_j)} \right] \right\} \times 100, \quad (7)$$

where S_{ij}^{direct} indicates the direct competitive intensity between importers v_i and v_j , k refers to the country that exports wheat to countries v_i and v_j together, Y_{ki} (Y_{kj}) denotes the gross volume that country v_i (v_j) import wheat from country v_k , Y_t represents world total import volume and Y_i (Y_j) indicates total import volume of country v_i (v_j). $(Y_{ki} + Y_{kj})/Y_t$ describes the competition pressure faced by wheat importers v_i and v_j . $1 - |(Y_{ki}/Y_i) - (Y_{kj}/Y_j)| / [(Y_{ki}/Y_i) + (Y_{kj}/Y_j)]$ measures the similarity of import structure of v_i and v_j where a larger value represents fiercer direct competition.

Furthermore, two importers without direct competition may indirectly compete with each other through their common neighbor country in the network. Here we take the path $v_i - v_h - v_j$, shown in Fig. 2 as an example. Though there is no direct competition between wheat importers v_i and v_j , changes of direct competitive relationships (v_i, v_h) and (v_h, v_j) may still affect the indirect competition between v_i and v_j . Due to the common competitor v_h , the importer v_i will indirectly compete with importer v_j . Similar to the competitive transmission path $v_i - v_h - v_j$, plenty of long transmission paths, like $v_i - v_p - \dots - v_q - v_j$, indeed exist through a series of mediators (v_p, v_q and so on). However, the competition between v_i and v_j would become unstable in the long competitive chain, especially facing some uncertain events. Thus, the indirect competition between two importers (v_i and v_j) that pass through only one mediator (i.e., one country) is considered in this study. Meanwhile, for v_i and v_j , there may be different indirect competition paths (each path having one mediator, like $v_i - v_h - v_j$), and different mediators may have different contributions to the whole indirect competitive intensity. The largest contribution indicates the mediator that plays the most significant role in stabilizing importers' trade. In this study, only the mediator that make the largest contribution to indirect competitive intensity among importers are analyzed. The indirect competitive intensity is given as follows:

$$S_{ij}^{\text{indirect}} = \sum_h^\phi \frac{1}{1/S_{ih}^{\text{direct}} + 1/S_{hj}^{\text{direct}}}, \quad (8)$$

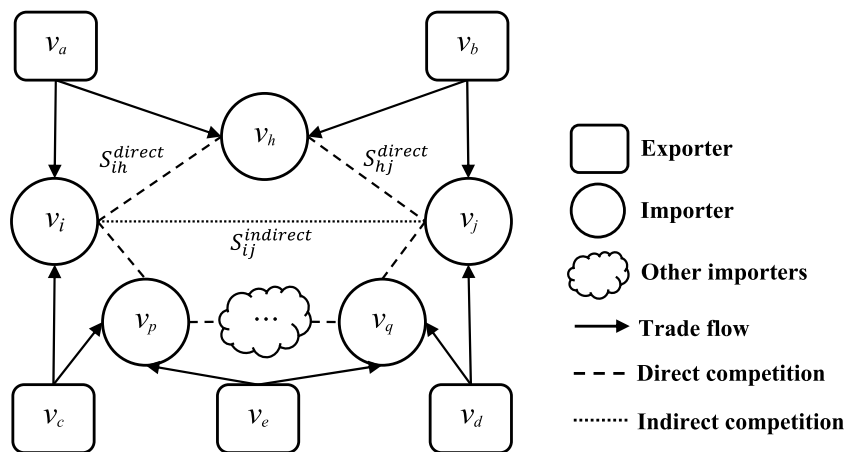


Fig. 2. Schematic of competitive relationships. The countries v_a, v_b, v_c, v_d and v_e in the boxes export wheat to the countries v_h, v_i, v_j, v_p and v_q in the circles. The cloud represents the set of possible existing importers in transmission path $v_i - v_p - \dots - v_q - v_j$. The solid line with arrow denotes the wheat trade flow, the dashed line describes the direct competition, and dotted line represents the indirect competition.

where $S_{ij}^{indirect}$ indicates the indirect competitive intensity between importers v_i and v_j , h represents the mediator v_h on the competition transmission path (for example the transmission path $v_i - v_h - v_j$ in Fig. 2) and Φ denotes the set of mediators.

2.4. Data for wheat trade competition network

We obtain wheat trade data from the *United Nations Commodity Trade Statistics Database* (UN Comtrade). This database contains over 3 billion data records reported by country and covers over 170 countries/areas. Due to different sources of information, there may be more than one values for a specific importer from a specific exporter. In such cases, we take the average volume. In this paper, we consider wheat-trading competition from 2004–2014 to capture the overall temporal trends of the evolution of the network. Each commodity has specific HS code and the wheat code we studied in this paper is 1001. 194 countries are included in the analysis.

3. Results and discussion

3.1. The overall analysis of competition network

With climate change, population growth and food demand increases [39,40], many countries, especially developing countries, import a large amount of wheat from other countries with large wheat production. This situation leads to global competitive relationships as illustrated in Fig. 3. However, most countries' gradually have fewer competitors over time (the degree value gradually decreases), which means that the competition faced by wheat importers has weakened. For example, median degree value (number of countries with a competitive relationship with a given country) decreased from 154 in 2004 to 135 in 2014.

In order to depict the global competition pattern by region, we analyze the competitive relationships among five continents by year, which is illustrated in Fig. 4. Each bar in Fig. 4 denotes the total number of links between two continents in a given year, and the higher the bar is, the stronger competition between the corresponding continents. The continents of less production strongly compete with other regions, which can be seen from the relationships in Africa, with a wheat production accounting for 3.6% of the world in 2014 [8] and other continents (the first column in Fig. 4). Asia has strong competition with Europe and Africa, likely because of large population (for instance, Asia has 59.86% of the world population in 2014 [41]). Due to a great demand for wheat import, the America and Europe also face fierce competitive pressure with other regions. However, except for the competition between Asia–Europe and intra-Europe, almost all competition among continents becomes weaker over time (2004 to 2014).

In order to describe network's competitiveness and how it changes with time, we calculated three indicators: density, average clustering coefficient and average path length. Results, as shown in Fig. 5, indicate that the value of density and average clustering coefficient are respectively around 0.65 and 0.9 (the maximum values are 1), and the value of average path length is around 1.33 (the minimum value is 1), which means fierce competition in the global wheat-trading competition network. Meanwhile, the value of density and clustering coefficient slightly decrease and the value of average path length increases over time. Such changes reflect that the number of direct competitive relationships among wheat importers is decreasing, and the network's competition gradually become weaker with time.

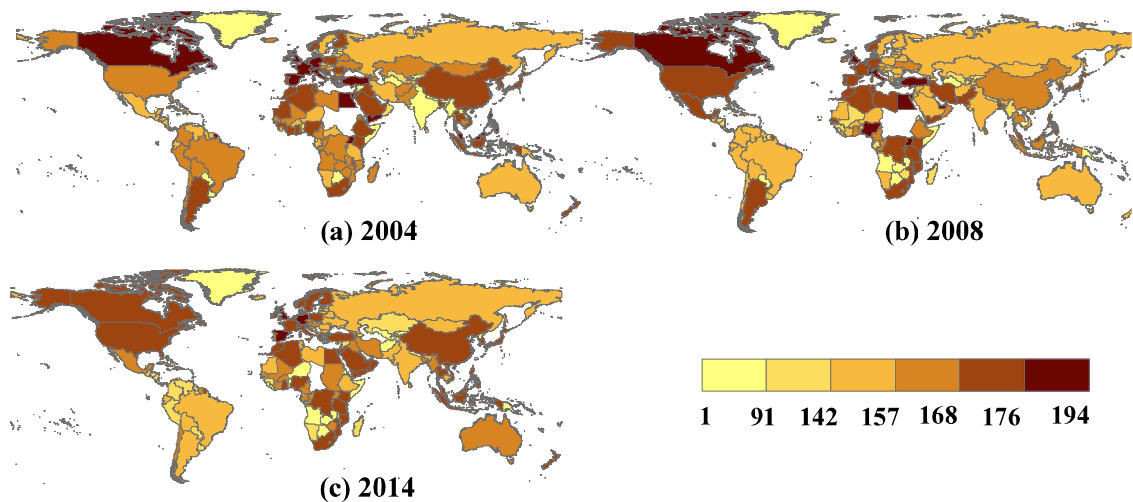


Fig. 3. The evolution over time of the global degree distribution for wheat. Degree indicates the number of links (i.e., number of countries for which the given country has a competitive relationship), with darker colors indicating a higher number of links. Countries that are shaded white indicate that data are not available. (a) 2004, (b) 2008, (c) 2014. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

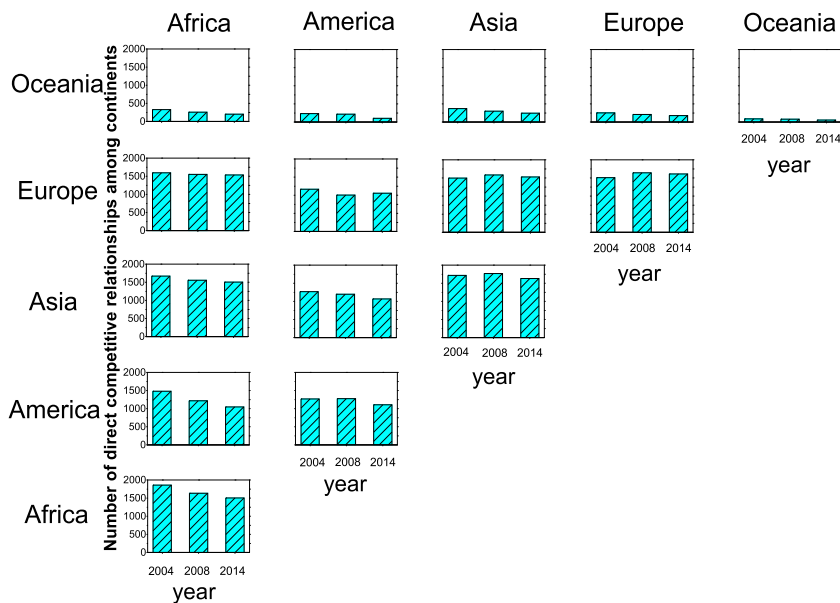


Fig. 4. The competition among different continents by year. Each bar in each panel denotes total number of links between two continents in each year.

To help us grasp the spatial distribution of main competitive regions, the core–periphery model can be applied to differentiate core wheat importers and periphery importers. In Fig. 6, with the increase of ρ (from 0.618 in 2004 to 0.699 in 2008, and to 0.709 in 2014), where ρ represents how well the core–periphery structure approximates an ideal core–periphery structure, the core–periphery structure becomes clearer. This shows that while core importers are distributed around the world, the main core competitive regions shifted a little bit. In 2004, the main core regions were concentrated in Central and South America, Africa, Asia and Europe, whereas North America gradually entered into the core in later years. The change of core regions results from the changes of import strategy for wheat importers. At the same time, some countries' roles (core or periphery) changed, as wheat is not only an essential resource to meet the domestic demand, but also an important strategic resource to maintain countries' stability in contemporary society. We take the US (periphery country in 2004, but core country in 2014) as an example. From 2004 to 2014, the amount of imported wheat increased, from 1.12 million tons to 3.53 million tons [8], and the import source countries also changed.

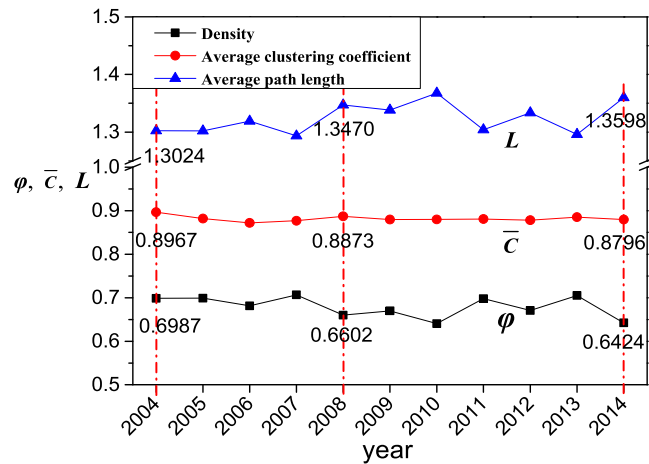


Fig. 5. The evolution of density (ϕ), average clustering coefficient ($\bar{C}$) and average path length (L) of the competition network.

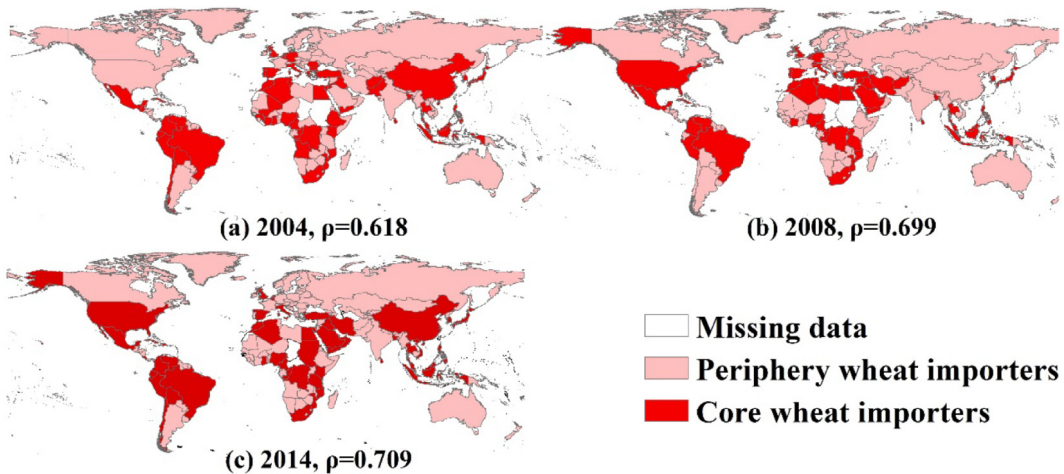


Fig. 6. The evolution of core-periphery structure in competition network. Red indicates core wheat importers, and pink denotes the periphery wheat importers. Countries that are shaded white indicates that data are not available. (a) 2004; (b) 2008; (c) 2014. ρ represents how well the core-periphery structure approximates an ideal core-periphery structure. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.2. The evolution of weighted competition network

3.2.1. The evolution of direct competition

Due to various import source and different import volume, the competitive intensity among importers may be different. Table 1 displays the top 10 fiercest direct competitive relationships in 2004, 2008 and 2014, from which we can find that fierce direct competitive relationships dramatically change over time, but the members that participate in their competitions are still concentrated in several large wheat importers (such as China, Japan, and Algeria). In 2004, the competitions between China (Asia) and other importers were substantial. However, with the adjustment of other countries' strategies, other countries, like Japan (in Asia) and Algeria (in Africa), gradually replaced China's position and played important roles in competitive relationships in 2008 and 2014. In short, though the competitions relationships change, the countries from Asia and Africa still play significant roles in fierce direct competition relationships and dominate the wheat competition.

In addition, the competition among large wheat importers plays an important role in the development of the wheat-trading competition pattern. Therefore, we selected eight main wheat importers (including developing and developed countries from different continents) to explore the evolution of competitive intensity (Fig. 7). As a whole, the value of competitive intensities decreased with year, but some turning points (the lowest point of "U-shape", like the polylines in the first panel of Fig. 7, decreasing before this point and increasing after this point) occurred in 2008 because of the demand

Table 1

The top 10 direct competitive relationships with the greatest competitive intensities.

Rank	2004	2008	2014
1	China–Japan	Algeria–Italy	Japan–Nigeria
2	Algeria–Italy	Japan–Mexico	Japan–Mexico
3	Japan–Mexico	Japan–Philippines	Algeria–Morocco
4	China–Venezuela	Algeria–Belgium	China–Indonesia
5	China–Colombia	Algeria–Morocco	Algeria–Belgium
6	China–Mexico	Japan–Thailand	Japan–Rep. of Korea
7	China–Egypt	Algeria–Netherlands	Indonesia–Rep. of Korea
8	China–Philippines	Italy–Egypt	Turkey–Egypt
9	China–Rep. of Korea	Indonesia–Japan	Algeria–Italy
10	Japan–Philippines	Japan–Rep. of Korea	Indonesia–Malaysia

Table 2

The top 10 intermediary wheat importers by year.

Rank	2004	2008	2014
1	China	Italy	Italy
2	Italy	Japan	Egypt
3	Egypt	Egypt	Japan
4	Japan	Indonesia	Indonesia
5	Algeria	Iran	Algeria
6	Indonesia	Algeria	Spain
7	Spain	Spain	Iran
8	Netherlands	Yemen	Bangladesh
9	Bangladesh	Rep. of Korea	Zimbabwe
10	Vietnam	Netherlands	Mexico

fluctuation. Take China as an example, owing to reduction of wheat import (decrease of 86.6%¹), the competitive intensities between China and other countries became weaker from 2004 to 2008. After 2008, although the global wheat price increased and the after-effects of financial crisis existed, China still imported a large quantity of wheat, which led to China's turning point in 2008. At the same time, the intensities among China, Japan, Indonesia, Rep. of Korea from Asia and other importers (especially the intensity between Japan and other importers) are relatively high, which illustrates that Asia increasingly plays a significant role in the evolution of the wheat competition network.

3.2.2. The evolution of indirect competition

The transmission of direct competition leads to potential indirect competition among importers without direct relationships and such indirect competition is closely related with mediator (the country that transmitting indirect competition relationships). Table 2 shows the countries that are the top 10 mediators, from which we can find that some large wheat importers, like Italy, Egypt, Japan and Algeria, always play significant roles in transmitting competition. These wheat importers diversify their wheat import sources and have direct competitions with most wheat importers. Thus, the possibility of indirect competition to pass through large wheat importers is great. High direct competitive intensities related to large wheat importers lead to their strong ability to transmit competition. However, the ranks of some importers in Asia, such as China and Vietnam, have declined over time (from top 10 to out of the top 10).

Furthermore, to better understand the indirect competition from mediators, six major intermediary countries, including Italy, Egypt, Japan, Indonesia, Algeria and Spain,² are chosen and the results are presented in Fig. 8. It is shown that Italy influences the most indirect competition, but the influence is declining. The number of indirect relationships affected by Egypt and Indonesia have increased, indicating its increasingly critical position in the global competition pattern. Besides, due to differences in factors (like geographical locations and import sources), the competitive regions affected by the mediators are clearly different. Italy has a global impact on competition transmission because of their relatively various import sources, while Egypt, Japan and Algeria only impact local regions. Egypt mainly influences the indirect competition among importers in the Asian and African regions, Japan mainly influences the indirect competition among importers in the Americas and African regions, and Algeria mainly influences the indirect competition among importers in the African and Europe regions. However, some influence regions are the continents where the mediators locate, while others are not. For example, Japan locates in Asia, while it mainly affects the Americas–Americas region. It is because that US and Canada are two largest wheat source countries for Japan and they are also indispensable parts for many countries from Americas, thus Americas–Americas (light green) becomes the main influence regions for Japan.

¹ The data is calculated from UN Comtrade's two-year (2004 and 2008) import volume.

² The indirect competitive relationships influenced by these six countries account for more than 50% in the total indirect competitive relationships among wheat importers.

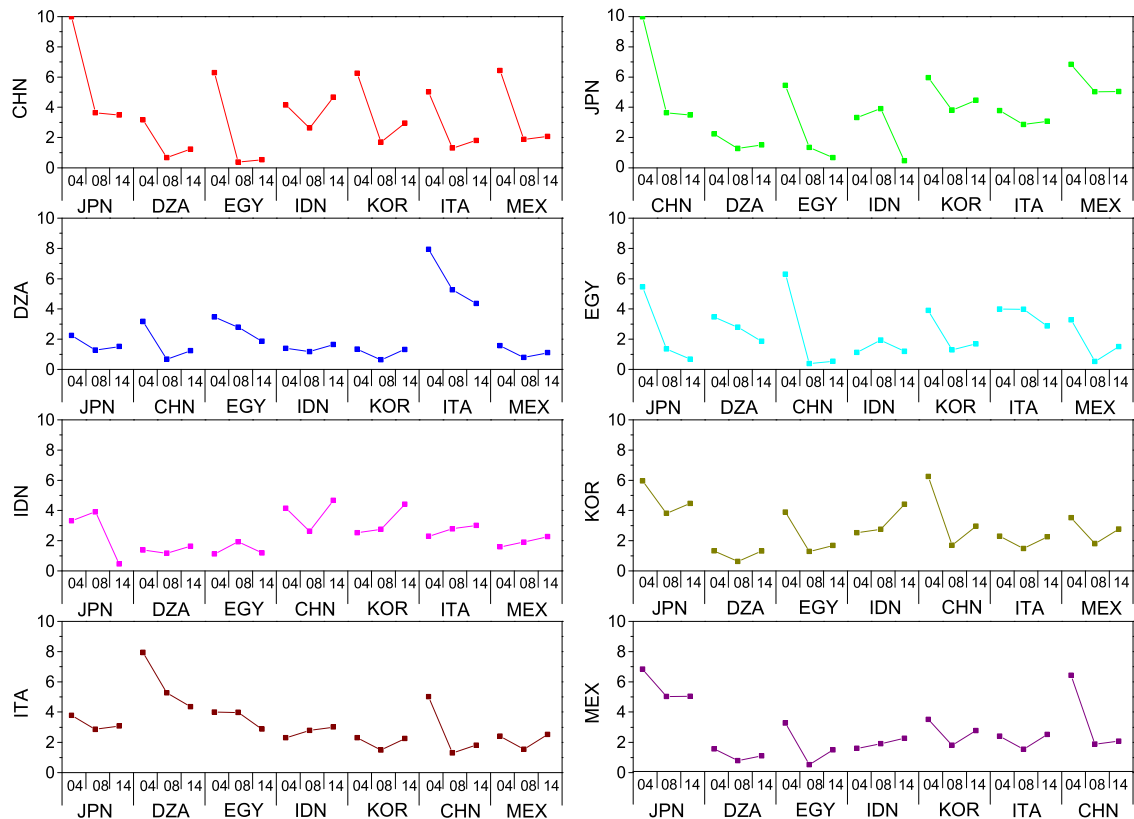


Fig. 7. The evolution of competitive intensity among eight large wheat importers (China (CHN), Japan (JPN), Algeria (DZA), Egypt (EGY), Indonesia (IDN), Rep. of Korea (KOR), Italy (ITA) and Mexico (MEX)). Each point in the panels represents the competitive intensity between two countries in a given year.

4. Conclusions

Most previous research focused on regional food trade relationships with less attention to global competitive relationship. In this paper, we constructed two types of wheat competition network based on complex network theory and gave a detailed analysis on wheat-trading competitive relationships. Results revealed that wheat trade had formed a global competition pattern, while the number and tightness of competitive relationships gradually decreased with time. Africa and Asia become the major influential regions, which was likely mainly due to their large wheat demand. A second finding was that, although core countries in the competition network were distributed around the world, the core-periphery structure of network became more defined with time. Thirdly, large wheat importers such as Italy, Egypt, Japan and Algeria, were the main driving force for evolution of the competition pattern and played important roles in transferring wheat-trading competition.

Facing global climate change and trade competition, each wheat importer should take appropriate actions to survive in new competitive environment. According to our results, some recommendations are put forward to promote the stability and healthy evolution of wheat-trading competition. First, environment. The stable operation of the wheat trade is based on free and healthy trade circumstances at home and abroad. A healthy competitive network is fostered by each country taking part in regional and global trade negotiations and promoting the formation of a global wheat-trading governance mechanism to make the global wheat trade more secure, stable and sustainable. Second, cooperation. The development of globalization in competition has strengthened the interactions among importers, resulting in wheat importers being linked by trade benefits. The adjustment of any wheat traders' import strategy will affect the competition faced by most other wheat importers and the stability of wheat trade, which could potentially affect countries' import security. Thus, the overall network is enhanced with cooperation. Third, development. Large wheat importers are the main wheat consumers and face more competitive pressure. For these countries, developing agricultural technology and improving wheat production may be the major tools to balance demand and supply and address climate change.

There are several limitations of this study, which provide opportunities for future research. Firstly, we analyzed the competitive relationships among wheat importers based on global trade relationships. However, some important factors, like oil price [42], water scarcity [43] and politics affecting global food trade have not been explicitly considered and could be investigated regarding their effects on global food trade. Secondly, other works could explore whether global organizations (e.g., APEC, EU, OECD and ASEAN) with strong economic influence affect the global food trade. Thirdly, this work considered

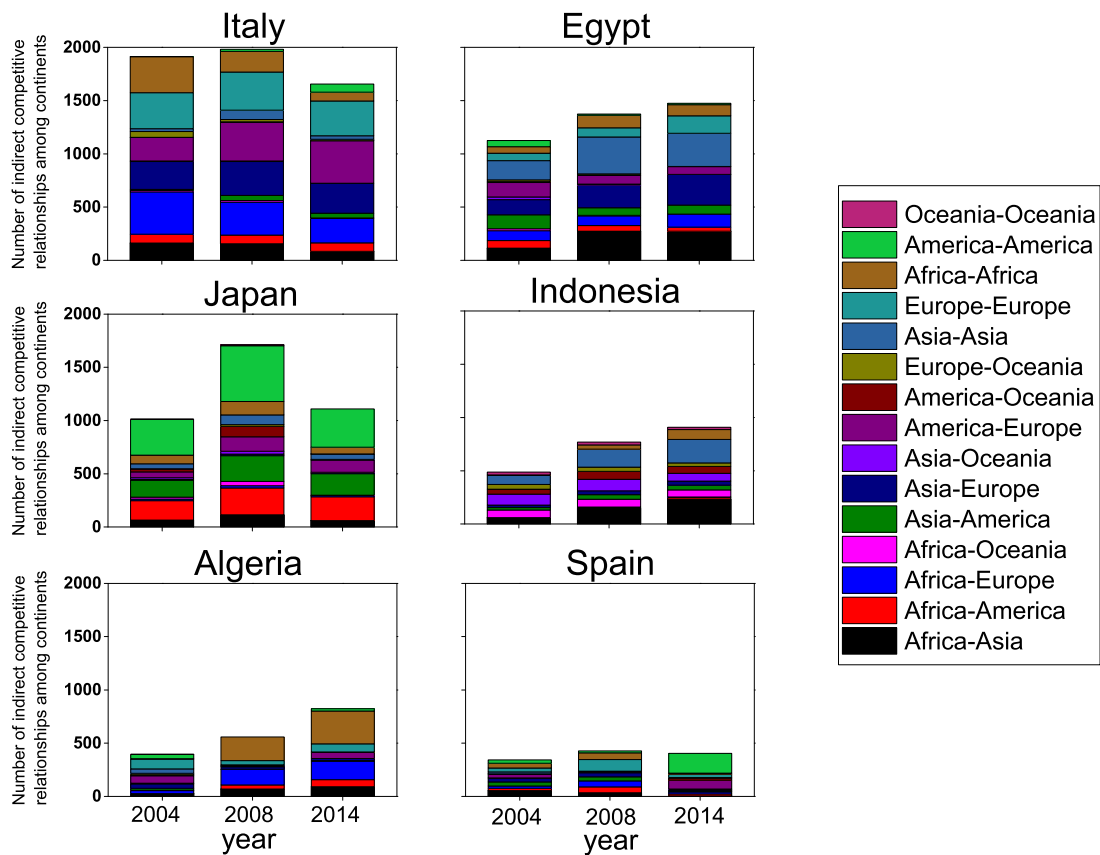


Fig. 8. The influence distribution caused by 6 major intermediary countries. Each stack bar and color respectively denote the sum and each number of indirect competitive relationships caused by specific country in one year. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

the competitive relationships among five regions (continents), but more regional divisions could be explored. Finally, our study focused on the competition from import perspective. However, several country may export wheat to one country, which leads to potential competition among these exporters. Studying the other kind of competition from export perspective may reveal more interesting evolutionary rules of trade competition.

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